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Elderly's heterogeneous responses to topographical factors in travel mode choice within a hilly neighborhood: An analysis based on combined GPS and paper-based surveys

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Because of the decline of physical abilities of the elderly, their mobility is more vulnerable to topographical factors than younger population groups. However, topographical factors have been neglected in studies on travel behavior, and elderly people's heterogeneous responses to topographical factors remain unknown. To fill this research gap, this study focuses on a hilly neighborhood called Koyo Newtown in Hiroshima City, Japan, where a multi-period (two waves) and multi-day (two weeks) panel survey was conducted in 2010 and 2011. The survey consisted of a GPS survey and a paper-based travel diary survey. In addition, a travel mode choice model is developed based on a panel mixed logit model. Heterogeneities are captured by introducing random effects to parameters of topographical factors, which are measured in terms of altitude difference, intensity of up/down movement, maximum slope, and changing slope. Furthermore, effects of introducing personal mobility vehicles (PM) to mitigate negative impacts of topographical factors are also evaluated. As a result, it is found that the altitude difference and maximum slope factors have significant impacts on mode choice decisions. The effectiveness of PM to support the mobility of elderly residents is also confirmed.

Keywords: *Topography, Elderly mobility, Travel mode choice, Panel mixed logit model.*

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1. Introduction

The aging phenomenon and its serious impacts on the elderly mobility and daily life have been observed in developed countries. People's physical abilities usually decline with age and impacts of such decline on the elderly's life are more serious in hilly and mountainous areas. In Japan, the target country of this study, the rapid population growth which took place in Japan from the 1950s to the 1980s led to the appearance of new neighborhoods, or so-called "newtowns", in suburban areas. Many of these newtowns were developed in hilly or mountainous areas. The aging of the population in Japan is more rapid than other developed countries. The elderly share in Japan (i.e., the share of population aged 65 years old or above) has reached 26% and the share even exceeded 30% in some prefectures[6]. The elderly share is even higher in mountainous areas. Many mobility problems have emerged in the aging newtowns: the decrease in the number of commuters has led to a reduction in the level-of-service of local public transport to central urban areas. Due to the decline of physical abilities, it is difficult for some elderly people to drive by themselves. Hilly/mountainous geographical features may further restrict elders' activity participation via trip generation, mode choice, route choice and so on because of difficulties to walk and abilities to use motorized travel modes. As a result, their daily mobility has to rely on others' pick-up and drop-off. After retirement, the elderly living in newtowns may not need to make long distance trips to working places, their activity space may tend to be smaller and there are probably more shorter-distance trips within newtowns. Such mobility issues have been under-researched and consequently insights into transport policy decisions are very limited, especially in hilly and mountainous newtowns. Therefore, there is an urgent need for greater research attention to travel patterns within aging newtowns. Such research is further motivated by the fact that traffic accidents of elders have happened mainly within about 500-meter periphery of their houses[7]. A better understanding of travel behavior within such a neighborhood may allow policy makers not only to make better decisions on the elderly mobility policy, but also to build self-contained neighborhoods for maintaining necessary facilities and services for the elderly's daily life.

The concept of self-containment was embodied in the planning objectives of many newtowns, especially in Europe and the United States. This concept was first promoted by Ebenezer Howard via the Garden City Movement, in which was planned as self-supporting communities (Howard, 1898, cited Cervero, 1995a) were planned in order to relieve London from overcrowding in the post-World War II period. Conventionally, it is usually interpreted as a balance between job and housing (i.e., job-housing balance) in a community. Taking a broader perspective, self-containment is considered as a form that allows people to live, work, go shopping and enjoy recreational activities within a community (Burby & Weiss, 1976, cited fromCervero, 1995a). In other words, it physically contains all necessary aspects of community life, including employment. From a planning and policy perspective, a high rate of self-containment level indicates that local residents are satisfied with a set of land use and transport conditions, contributing to reducing automobile use and thus devoting to regional environmental sustainability (Yigitcanlar *et al.*, 2008). Healy and O'connor (2001) suggest that "smart urbanization could really mean self-contained suburb development, and a smart policy could be one that enhanced suburban self-containment". This stream has resulted in a number of studies discussing self-contained neighborhoods with regard to commuting trips (Cervero, 1995a; Curtis & Olaru, 2010; Hui & Lam, 2005; Merlin, 2014; Miller, 2011; Yigitcanlar *et al.*, 2008). In terms of self-containment arguments of newtowns, some researchers focus on non-work trip patterns (Lee & Ahn, 2005; Merlin, 2014), while others address both work and non-work trips (Jun, 2012; Pakzad *et al.*, 2007). Especially in non-work trips, availability and attractiveness of

[6] http://www8.cao.go.jp/kourei/whitepaper/w-2015/html/gaiyou/s1_1.html (Accessed July 25, 2016)
[7] http://www.mlit.go.jp/road/ir/ir-council/life_road/pdf01/4.pdf (Accessed July 25, 2016)

travel modes within newtowns would affect destination choices, which eventually determine the level of self-containment. Bearing this in mind, we conducted an experiment to confirm the impacts of personal mobility vehicles (PM) in a newtown on travel mode and destination choices (Chikaraishi *et al.*, 2015).

The literature on the relationship between travel behavior and local geographical environment has grown considerably over the last two decades (e.g., Badoe & Mille, 2000; Crane & Crepeau, 1998; Ewing & Cervero, 2001). In these studies, the local geographical environment is understood as natural and built environments, such as local topography, street characteristics, availability of sidewalks, sidewalk width and so on. Travel mode choice studies have illustrated this relationship. If the local geographical environment supports the use of a travel mode, then such a mode can be provided adequately for the neighborhood (Rodrı□guez & Joo, 2004). Recent studies have shown that certain attributes of the local physical environment can affect the attractiveness of travel modes, especially for non-motorized modes (Cervero & Duncan, 2003; Handy & Xing, 2011; McGinn *et al.*, 2007; Olszewski & Wibowo, 2005; Rodrı□guez & Joo, 2004). For example, Rodrı□guez and Joo (2004) argue that the slope does not influence the attractiveness of travel mode by adding the time difference without and with slope information into a mode choice model. They find that the slope information has a significant impact on non-motorized mode choice. Cervero and Duncan (2003) introduce a slope variable, defined as rise/run ratio between origin and destination, to a mode choice model, and find that it significantly affects walking. Sousa *et al.* (2014) consider a slope effect on bicyle usage, where the slope was evaluated by respondents using a seven-point Likert scale as a perception of barriers. By using a shank-mounted inertial measurement unit, slope is computed by horizontal and vertical displacements, and the slope affect walking speed (Li *et al.*, 2010). Socharoentum and Karimi (2016) simulate the route choice for walking with considering an impact of slope defined as a slope for each context-aware walking segment, while Broach *et al.* (2012) examine an effect of 10-meter increments along each link for cycling route choice. A hypothetical binary route choices for bicycling base on a experiment with an attribute of route slope (Motoaki & Daziano, 2015). Mohanty and Blanchard (2016) also examine the impacts of slope on bicycle/walking access to transit, where slope is calculated along the shortest path between origin and destination. However, most studies focus only on walking and bicycle, and it has remained unclear how PM can alleviate physical burden of slope. Thus, topographical factors have been under-researched in the literature of travel behavior. More seriously, the elderly's heterogeneous responses to topographical factors has remained unknown.

To fill the above research gap, as an initial step to explore the comprehensive travel behavior in a neighborhood, this study focuses on a hilly neighborhood, called Koyo Newtown, Hiroshima City, Japan, and attempts to examine the effects of topography factors (e.g., altitude and slope) on the elderly travel mode choices, including a new short-distance travel model, i.e., PM. For this research purpose, a multi-period (two waves) and multi-day (two weeks) panel survey was conducted in 2010 and 2011, which consists of a GPS survey and a paper-based travel diary survey. The GPS survey records travel behavior trajectories (coded by latitude and longitude) through GPS devices. Such GPS survey allows us to examine the impacts of topographical factors on travel mode choices, including PM choice under actual situations.

The remaining part of this paper is organized as follow. The multi-period and multi-day panel survey is described first, followed by explanations about the panel data used in this study and discussion of preliminary aggregation analyses. Next, a panel mixed logit model is built to represent travel mode choice behavior by focusing on the impacts of newtown topography and the elderly's heterogeneous responses to topographical factors. Furthermore, model estimation results are explained and implications of results are discussed. Finally, this study is concluded by summarizing the findings and discussing directions of future research.

2. Survey and data

2.1 Survey

The survey area is Koyo Newtown located in a hilly suburban area of Hiroshima City, Japan. Koyo Newtown (current population: 17,000) is located in the north-east part of the city, about 11 kilometers away from the city center. Koyo Newtown is a typical aging newtown in Japan, characterized by steep slopes (the community center is located on the top of the hill) and a high proportion of elderly residents (currently the ratio of the elderly, who are 65 years old and over, to total population is around 26.7%). While there are railway and bus services to the city center, public transport services within the newtown are relatively poor. The newtown has a better self-containment than others in Japan in the sense that community hall, shopping center, post office, banks, hospital and sports club are all located in the community center.

Although Koyo Newtown administratively consists of four districts (Magame, Kamezaki, Ochiai, and Kurakake), the survey was conducted only in Magame and Kamezaki where the newtown center is situated (Figure 1). As can be seen in Figure 1, where some examples of trips from the survey (O_1-D_1, O_2-D_2: blue lines) are also shown, the community center is located on the top of a hill. Such geographical features force the residents to move up and down to go to the center. Thus, topography may have a potential influence on the elderly's mode choices in the study area.

For the research purpose, a panel survey was carried out in 2010 and 2011. Considering that the elderly may tend not to make regular daily trips after retirement, a longer period is needed to trace their trip-making. As a result, a multi-day travel diary is adopted for capturing infrequent and irregular trips. To examine the effects of PM on mitigating the topography-induced burden of the elderly, a social experiment was also conducted, where a newly developed PM, as shown in Figure 2, was provided to residents. In principle, PM was given to respondents who want to use it, and in total there are 10 respondents use PM in the second wave. Each wave includes two weeks.

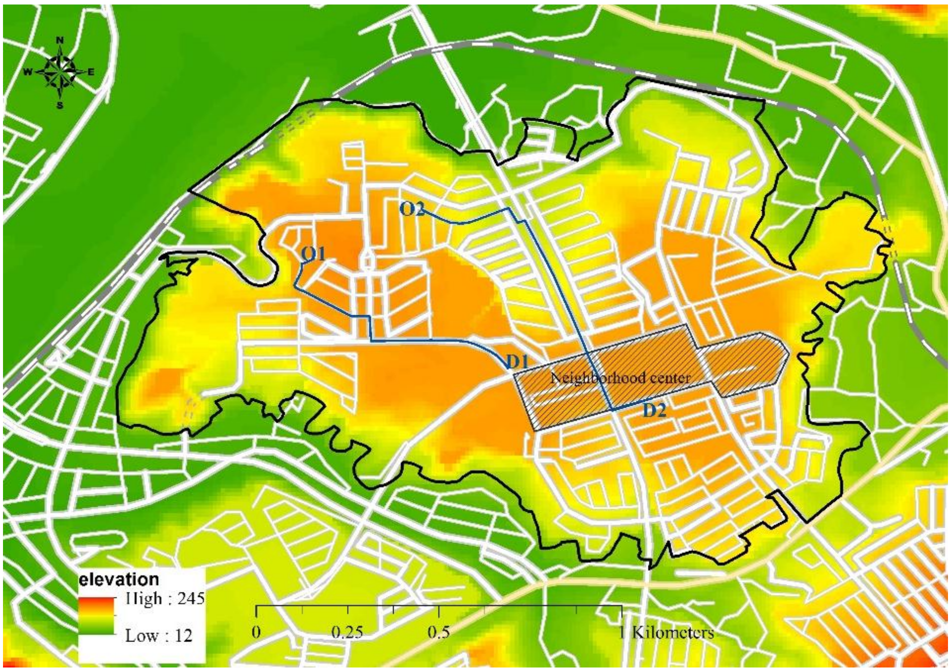

Figure 1. Study area: Koyo Newtown in Hiroshima City, Japan

PM types / Characteristics	 (a) power-assisted two-wheeled bicycle	 (b) power-assisted three-wheeled bicycle	 (c) mobility scooter
Vehicle size (length × width × height [mm])	1,875×580×1,025	1,755×600×1,120	1,090×550×1,070
Engine	Electric power assist		Electric motor
Maximum speed	-	-	6.0 km/h
Distance per charge	Around 15km	Around 25km	
Driving license	Not required		

Figure 2. Personal mobility vehicles (PM) used in the experiment

With the support of Hiroshima City government and social welfare councils in Magame and Kamesaki, the survey was conducted to households with at least one elderly member (60 years old and over). During the two-week survey period at each wave, household members were asked to fill out a paper-based travel diary, while one elderly member of each household was requested to record each trip trajectory using a GPS logging device. More specifically, the two-week travel diary in the first wave was designed based on the German Mobility Panel[8]. It is found that some respondents answered the diary survey incorrectly in 2010. Most participants also commented on the diary. To reflect these issues and concerns, the travel diary in the second wave was revised based on the Survey in Time Use and Leisure Activities[9] implemented by the Ministry of Internal Affairs and Communications in Japan. Around 50 households participated in each wave, with 38 households common to both waves.

2.2 Data

Here, panel data from elderly respondents are used. Among the 38 respondents remaining in the two waves, 31 provided valid GPS data and 26 recorded paper-based data. While paper-based data provide trip purpose and travel mode information that cannot be collected through GPS devices, GPS data provide precise activity location information. To make full use of the advantages of the two sets of surveys, GPS data and paper-based data were merged.

For GPS data processing, first, trip ends are detected within GPS data stream by searching for time periods of non-movement. The GPS data (decomposed into trips) and paper-based data are then merged based on departure and arrival time information. There are numerous studies which have identified thresholds in detecting trips and merging GPS data with paper-based data. These thresholds vary primarily depending on the characteristics of local activities. Wolf *et al.* (2001) state that two-minute threshold yielded the best prediction of the true trip ends. It is considered as a gap whenever the time interval or the distance between consecutive points is greater than two minutes or 250 meters (Chen *et al.*, 2010). A trackpoint is removed when the distance between two consecutive trackpoints is less than 10 meters (Bohte & Maat, 2009). Schüssler and Axhausen (2008) also use a two-minute threshold to record stopped activities. Based on the findings of existing studies, this study considers that a movement is regarded as a trip when it is more than 100 meters within two minutes, and uses a time-interval condition with 30 minutes threshold to merge the two kinds of data. As a result, a total of 1,684 trips is identified in the two waves.

This study only uses trip data, in which origins and destinations are located within the boundary of Koyo Newtown (created by adding a 200-meter buffer to the administrative boundary). As a

[8] http://daten.clearingstelle-verkehr.de/192/ (Accessed July 26, 2015)
[9] http://www.stat.go.jp/english/data/shakai/2011/yogo.htm (Accessed July 26, 2015)

result, 1,015 trips are identified. The share of trips within the newtown is 60.3%, indicating that more elders tend to make a trip inside the newtown.

The shortest route was used to obtain topography information (i.e., slope and elevation) in this study. The survey area is Koyo Newtown where the route network follows by the layout of the newtown, there is a few of route choice. To some extent, once an origin and a destination are selected, then the route choice of the trip is automatically decided. The road network employed in this study is a digital road map of Japan released by the Digital Road Map Association. Specifically, to calculate the newtown topography data, (1) a shortest path as a polyline is divided into continuous points with a 10-meter segment, and (2) the slope of each segment is measured by the changes of altitude position data at 10-meter grid cell obtained from the Fundamental Geospatial Data of the Geospatial Information Authority of Japan. Out of the total, 55 trips were excluded because of missing information about travel modes and inabilities to calculate shortest routes. As a result, the total number of trips in this study is 960 trips. Note that, ideally, it would be better to estimate a route choice model with slope information and then add the expected minimum travel cost (including the cost of slope) into a mode choice model so that all potential routes with different slopes can be considered in the mode choice model. On the other hand, in order to do it, at least the path enumeration problem is needed to be solved. Although recent studies indicate the possibilities to overcome this limitation (Fosgerau *et al.*, 2013; Mai, 2016; Mai *et al.*, 2015), since it lies outside of the scope of this paper, we decided to use the shortest-path information in the current paper. Note that we checked how many trips actually use the shortest paths. The results indicate that around 62% of observed paths are matched with the shortest paths.

Figure 3 shows some examples of changes in elevations during trips. As can be seen, there is a stable altitude during the trip O_1-D_1, while the altitudes of the O_2-D_2 trip first decrease by about 15 meters to the lowest altitude, then rise by approximate 20 meters to the peak, and finally stablizes. In this case, topography information calculated only from the location of the origin and destination information would not reflect the up-down movement of the trip. This is one of merits to merge GPS and paper-based data. In this paper, four indicators are introduced to capture topographical features: altitude difference (*AD*), maximum slope (*MS*), intensity of up/down movement (*IUD*), number of changing slopes (*CS*).

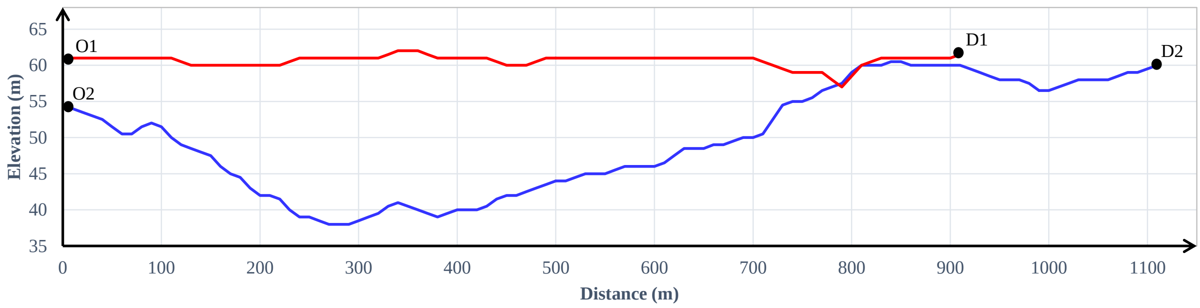

Figure 3. Some examples of changes in elevations during trips

Suppose that a t-th trip (t = 1, 2, …, T) has consecutive lines k (k = 1, 2, …, K), where each line was created by merging 10-meter continuous segments with the same slope s_k (see Figure 4 for the graphical visualization). Thus, the total number of lines K indicates the number of changing slopes (*CS*). Denoting that the elevation at a point changing slope is h_k (k = 1, 2, …, K+1), where k = 1 and $k = K + 1$ indicate origin and destination points respectively, other topographical features can be defined as follows:

$$AD_t = \max(h_{tk}) - \min(h_{tk}); \qquad (k = 1, 2, \ldots, K+1) \tag{1}$$

$$MS_t = \max|s_{tk}|; \qquad (k = 1, 2, \ldots, K) \tag{2}$$

$$IUD_t = \frac{\sum_k |s_{tk}|}{CS_t}; \qquad (k = 1, 2, \ldots, K) \tag{3}$$

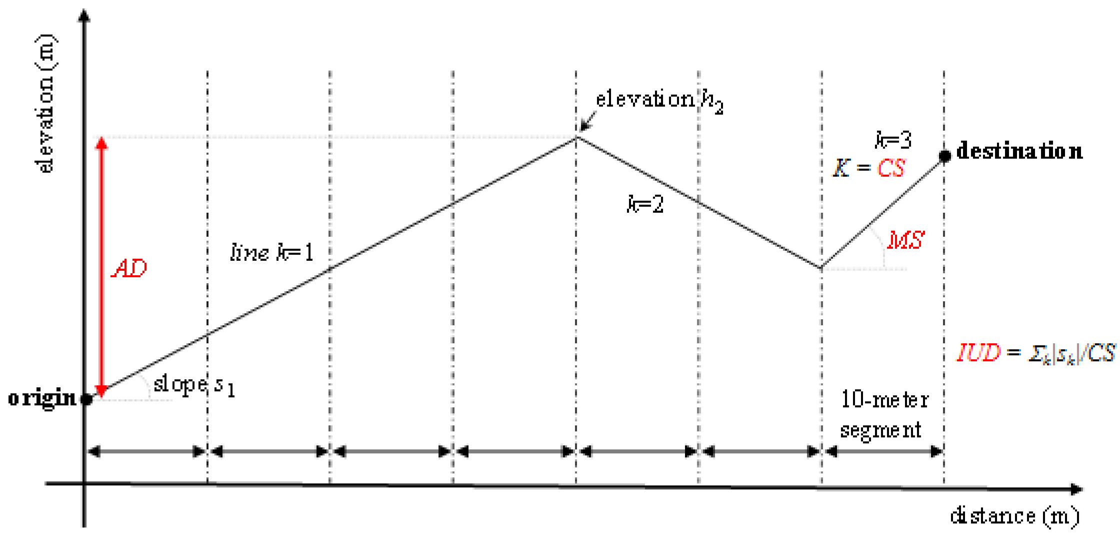

Figure 4. Illustration of four topographical indicators used in this study

Figure 4 describes these four indicators graphically. The four topographical variables indicate different aspects/phenomena of topography, which share some physical aspects. Therefore, multicollinearity should be concerned. The severity of multicollinearity is quantified by a variance inflation factor (VIF) to measure how much the variance of an estimated regression coefficient is increased because of multicollinearity. According to the recommendations of several studies (Hocking, 2013), individual VIF values greater than 10 and/or average VIF greater than 6 suggest strong collinearity. In our study, individual VIFs range from 2.45 to 5.29, with an average VIF of 3.99, suggesting that there is no serious problem of multicollinearity.

Table 1 shows basic statistics on share of travel modes. Car and non-motorized modes (walking and bicycling) are two biggest modes with the respective shares being 42% and 40.6 %, followed by PM mode with 12.3%. In contrast, the share of public transport just accounts for 2.2%. This partially points out poor public transport services in the newtown. Non-motorized modes, PM, and car are thus selected in the mode choice model, with 911 trips for the three alternatives (see Section 4).

Table 1. Share of travel mode

Travel mode	Number	Share (%)
Non-motorized mode	390	40.6
Personal mobility (PM) mode	118	12.3
Car	403	42.0
Public transport	21	2.2
Motorbike	25	2.6
Others	3	0.3
Total	*960*	*100*

It should be noted that health condition and physical abilities were considered in the both waves of the survey. This is because these aspects may have implications for elderly travelers

(Hildebrand, 2003; Su & Bell, 2009; Wasfi *et al.*, 2012). Particularly, aggregation analyses show that over 90% of the respondents can walk more than 200 meters without taking a rest and consequently do not need someone's help in daily life. It is also revealed that respondents going to hospital are less than twice a month account for around 70%. Considering the small variations in these results, the elderly's health and physical conditions are approximated by an age variable in this study.

3. Modeling travel mode choice

In order to examine the impacts of topographical factors on mode choice while controlling for other influential factors, a mode choice model is developed based on a panel mixed logit model (also called random-parameter logit) to account for unobserved heterogeneities among respondents who repeated choices over a certain period. For non-random (or observed) factors, individual characteristics, distance, and topography are considered. A number of studies have proven that individual socio-demographic factors relatively affect mode choice decision (e.g., Kitamura *et al.*, 1997, Susilo, 2007). Additionally, topography (e.g., slope information) is widely used, because it can be directly associated with policy discussions, especially to support walk and bicycle (Rodrı□guez & Joo, 2004). To the authors' knowledge, there was only one study examining topographical impacts on mode choice based on a mixed logit model (Mohanty & Blanchard, 2016).

The utility U_{njt} that an individual n (n = 1, 2, …, N) traveling on a t-th trip (t = 1, 2, …, T) chooses a travel mode j (j = 1, 2, 3) may be written as follows.

$$U_{njt} = \alpha_j + \eta_{nj} + \boldsymbol{\beta}\boldsymbol{X}_{njt} + \left(\boldsymbol{\gamma}_j + \boldsymbol{\varphi}_{nj}\right)\boldsymbol{Z}_{njt} + \varepsilon_{njt} \tag{4}$$

Here, α_j is a fixed constant term, and η_{nj} is a random component that is assumed to be normally distributed with mean 0 and variance $(\sigma_{\eta j})^2$. η_{nj} is used to capture individual-specific unobserved heterogeneity. $\boldsymbol{\beta}$ is a vector of coefficients associated with explanatory variables ($\boldsymbol{X}_{njt}$), $\boldsymbol{\gamma}_j$ and $\boldsymbol{\varphi}_{nj}$ are a vector of fixed coefficients and a vector of random coefficients respectively, both of which are associated with topographical variables ($\boldsymbol{Z}_{njt}$). The m-th element of $\boldsymbol{\varphi}_{nj}$, i.e., $\boldsymbol{\varphi}_{njm}$, is assumed to be normally distributed with mean 0 and variance $(\boldsymbol{\sigma}_{\gamma jm})^2$, which capture individual-specific unobserved heterogeneities with respect to topographical factors. ε_{njt} is an error term with a Gumbel distribution.

Conditional on η_{nj} and $\boldsymbol{\varphi}_{nj}$, the probability that individual n chooses mode choice j can be written as the following standard logit formulation. The dummy variable ρ_{njt} is equal to 1 if j is non-motorized mode/car. When j is PM, ρ_{njt} is equal to 1 if PM owned by individual n who travels on a t-th trip, and 0 otherwise.

$$P_{njt}\left(\boldsymbol{\beta},\boldsymbol{\gamma}_j \mid \eta_{nj},\boldsymbol{\varphi}_{nj}\right) = \prod_t \frac{\mathrm{e}^{\boldsymbol{\beta}\boldsymbol{X}_{nit} + \left(\boldsymbol{\gamma}_i + \boldsymbol{\varphi}_{ni}\right)\boldsymbol{Z}_{nit}}}{\sum_j \rho_{njt}\mathrm{e}^{\boldsymbol{\beta}\boldsymbol{X}_{njt} + \left(\boldsymbol{\gamma}_j + \boldsymbol{\varphi}_{nj}\right)\boldsymbol{Z}_{njt}}} \tag{5}$$

The likelihood function is formulated as,

$$L_{njt}\left(\boldsymbol{\beta},\boldsymbol{\gamma}_j \mid \eta_{nj},\boldsymbol{\varphi}_{nj}\right) = \int\int\prod_N\prod_j P_{njt}\left(\boldsymbol{\beta},\boldsymbol{\gamma}_j \mid \eta_{nj},\boldsymbol{\varphi}_{nj}\right)^{\delta_{njt}} f\left(\eta_{nj} \mid \sigma_{\eta j}\right) f\left(\boldsymbol{\varphi}_{nj} \mid \boldsymbol{\sigma}_{\gamma j}\right) d\eta_{nj} d\boldsymbol{\varphi}_{nj} \tag{6}$$

where N (=911) is the number of samples. The dummy variable δ_{njt} is equal to 1 if j is chosen by individual n who travels on a t-th trip, and 0 otherwise.

Simulation methods are often used to estimate a mixed logit model (e.g., Bhat, 2001; Chikaraishi *et al.*, 2011; Train, 2009). In this study, a hierarchical Bayesian procedure based on Markov Chain

Monte Carlo methods is employed (Train, 2009). In particular, the posterior distribution is written as,

$$K_{njt}\left(\boldsymbol{\beta},\boldsymbol{\gamma}_j,\sigma_{\eta j},\boldsymbol{\sigma}_{\gamma j}\,|\,\eta_{nj},\boldsymbol{\varphi}_{nj}\right)=\prod_N\prod_j L_{njt}\left(\boldsymbol{\beta},\boldsymbol{\gamma}_j\,|\,\eta_{nj},\boldsymbol{\varphi}_{nj}\right)^{\delta_{njt}} f\left(\eta_{nj}\,|\,\sigma_{\eta j}\right)f\left(\boldsymbol{\varphi}_{nj}\,|\,\boldsymbol{\sigma}_{\gamma j}\right)\phi\left(\sigma_{\eta j}\right)\phi\left(\boldsymbol{\sigma}_{\gamma j}\right)\phi\left(\boldsymbol{\beta}\right)\phi\left(\boldsymbol{\gamma}_j\right) \tag{7}$$

where an inverted Gamma distribution N(0.001, 0.001) is assumed for $\phi(\sigma_{\eta j})$ and $\phi(\boldsymbol{\sigma}_{\gamma j})$, and a normal distribution N(0, 1e-6) for $\phi(\boldsymbol{\beta})$ and $\phi(\boldsymbol{\gamma}_j)$ as a prior distribution. The terms $f(\eta_{nj}\,|\,\sigma_{\eta j})$ and $f(\boldsymbol{\varphi}_{nj}\,|\,\boldsymbol{\sigma}_{\gamma j})$ generate hierarchical procedures in the sampling process.

The model estimation is done by using WinBUGs (1,000,000 interactions with 500,000 interactions for burn-in, and 20,000 draws). The stationary distribution of the estimation results reported in this paper was tested in several ways, including (1) checking the trace plot and correlation in each parameter chain, and (2) using the Geweke diagnostic (Geweke, 1992). All results of the above ways show that the model reported in this paper is converged.

4. Estimation results and discussions

Table 2 shows explanatory variables introduced in this paper. *Socio-demographic* variables include age, gender, car ownership, and job. With regard to *distance* variables (the distance is used for all mode choices), it is the actual distance extracted from GPS logging device for each route. The following *topography* variables are determined by shortest paths with a 10-meter segment, and altitude with 10-meter grid cell as mentioned in Section 2.

Table 2. Explanatory variables

Explanatory variables	Definition	Mean	SD
Socio-demographic			
Age	< 65 years of age (1= yes; 0 = no)	0.189	0.392
Car ownership	Car ownership (1 = yes; 0 = no)	0.807	0.395
Male	Gender (1 = male; 0 = female)	0.759	0.428
Non-worker	Job (1 = retirement/jobless; 0 = otherwise)	0.833	0.373
Distance	Distance, km	0.825	1.401
Topographical factors			
Altitude difference	Maximum elevation - minimum elevation: m	16.730	14.138
Intensity of up/down movement	Intensity of up/down movement: degree	4.494	2.330
Maximum slope	Maximum slope: degree	12.660	9.235
No. of changing slopes	Number of changing slopes	43.970	35.475

The selection of explanatory variables was done step by step as follows. First, we estimated a multinomial logit model (MNL) only with *socio-demographic* variables, and the excluded insignificant variables from the model (at the 90% significant level). Next, we introduce distance variables by dropping insignificant variables. Finally, the four topographical variables are added to the model. We estimated both the MNL and a panel mixed logit (ML) models with the selected variables based on the above procedure. It should be noted that the MNL results are the same as the ML model without η_{nj} and $\boldsymbol{\varphi}_{nj}$. The results only with the 2nd wave data are similar with ones with the both waves' data, while some of the variables are not statistically significant presumably due to the relatively small sample size.

Table 3 summarizes the estimation results of MNL and ML models. The results are considerably different in terms of statistical significance of parameters. All *socio-demographic* variables, except car ownership, become insignificant after adding random components. This is because of the existence of unobserved heterogeneities among respondents that were not captured in the MNL model. This indicates that the significance of *socio-demographic* parameters in the MNL model is overestimated. Looking at the ML results, as expected, the *distance* variables are statistically significant with negative signs as expected, implying that respondents traveling longer distance are less likely to choose non-motorized modes and PM. This result is consistent with the fact that people prefer traveling by car for longer distance than walking and cycling. For *socio-demographic* variables, only the car ownership variable is statistically significant with a positive sign, indicating that travelers having a car are more likely to use it in comparison with other modes. This result is similar to a range of previous studies. Regarding the *topography* variables, altitude difference (*AD*) and maximum slope (*MS*) variables are statistically significant. Concretely, higher altitude difference results in higher PM use and lower non-motorized mode use, indicating that PM is the preferable mode in the hilly neighborhood. On the other hand, the higher maximum slope may reduce PM use, presumably because PM has limited power assistance. In this sense, PM could be particularly useful in areas which are hilly, but not in areas which have very steep slopes. For the random component of topographical variable $\boldsymbol{\varphi}_{nj}$, we introduce it to the intensity of up/down movement variable; however, it is estimated insignificant. The random parameters of constant terms are statistically significant. Since variance $(\boldsymbol{\sigma})^2$ is always positive, some studies state some other ways to assess statistical meaning for variance of random effect (Chikaraishi *et al.*, 2009; Pinheiro & Bates, 1995). Goodness-of-fit was assessed with both Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) shows that the ML model is far better than the MNL model.

Table 3. Estimation results of the mode choice model

Variables	Mode Alternatives	Multinomial Logit (MNL)		Mixed Logit(ML)	
		Parameter	*t* - value	Mean	Pseudo *t* - value
Constant term	Non-motorized	3.447	10.286	5.317	4.726
Constant term	PM	0.547	0.803	3.663	1.279
Socio-demographics (β)					
Age	Non-motorized	-1.245	-5.615	-2.003	-1.446
Car ownership	Car	0.986	4.200	1.146	2.904
Male	Non-motorized	-0.277	-1.213	-1.755	-1.519
Male	PM	2.482	4.025	-0.169	-0.056
Non-worker	Car	1.116	3.898	0.826	0.717
Distance variables (β)					
Distance	Non-motorized	-1.775	-8.732	-2.158	-7.999
Distance	PM	-1.095	-3.058	-2.210	-3.780
Topographical factors (γ)					
Altitude difference (*AD*)	PM	0.115	4.184	0.123	2.909
Altitude difference (*AD*)	Car	0.020	2.707	0.031	3.009
Intensity of up/down movement (*IUD*)	PM	0.124	1.477	-0.086	-0.339
Maximum slope (*MS*)	PM	-0.018	-1.821	-0.140	-2.294
No. of changing slopes (*CS*)	PM	-0.100	-2.613	-0.005	-0.332
Random effects (σ)					
Individual $(\sigma_\eta)^2$	Non-motorized			6.789	2.262[a]
Individual $(\sigma_\eta)^2$	PM			12.100	0.542[b]
Intensity of up/down movement $(\boldsymbol{\sigma}_\gamma)^2$	PM			0.225	0.496[c]
Sample size		911			
Initial log-likelihood		-1000.84			
Log-likelihood for model with only constant terms		-737.96		-737.96	
Log-likelihood for estimated model		-563.28		-372.32	
AIC		1154.56		778.64	
BIC		1167.99		794.95	

Note: Car is a reference alternative during model estimation; The posterior mean was divided by the posterior standard deviation to produce a pseudo t-value. Note also that the lower and the upper (2.5%; 97.5%) limits of the 95% symmetric credible interval of variances are *a* (2.835; 14.190), *b* (0.024; 56.190), and *c* (0.002; 1.244)

The findings mentioned above are also supported by respondents' satisfaction with local geographical environment. From the travel diary in 2010, it is found that approximately 85% of respondents were dissatisfied with traveling by foot and bicycle due to many slopes. This assessment demonstrates that topographical factors such as slopes may be a major barrier to restrict elderly' trip-making.

5. Conclusions

In Japan, newtowns were built around 40 years ago mostly during the period of the rapid population growth. A shrinking and aging population have recently been observed in these newtowns. This phenomenon is creating new challenges for mobility due to the reduction of level-of-services of local public transport and the limitations in elderly residents' capacities to drive and walk. A large proportion of residents in these newtowns are not commuters. Such a characteristic may increase the demand for activities inside newtowns. Considering the decline of elders' physical abilities, local geographical environment (e.g., local topography, street characteristics, availability of sidewalks, sidewalk width) needs to be taken into account in analyzing their travel behavior.

This study has examined the impacts of newtown topographical factors (altitude difference, intensity of up/down movement, maximum slope, and changing slopes) on elderly' mode choices within a hilly newtown in Japan. A mode choice model was developed by using a multi-period and multi-day panel survey data collected in a typical hilly newtown located in Hiroshima, Japan. It is found that the altitude difference and maximum slope factors, among four topographical factors under the study, have significantly impacts on elderly's mode choice decisions. The usefulness of elderly-oriented personal mobility vehicles (PM) in mitigating the negative effects of topographical factors is also revealed. The study suggests that policies to introduce PM into hilly newtowns can potentially contribute to the mobility of elderly residents.

The current study has provided useful insights into future urban and neighborhood planning. However, there are surely a number of unresolved research issues. First, for capturing a more general picture of travel behavior in a neighborhood, route choice should be targeted. This is because different parts of a route may have different topographical elements as discussed in Section 2. Second, topographical factors may affect the elderly's car ownership, which may be further affected by their car ownership and usage when they were young, and residential location choices, which are usually influenced by residential environment (including topographical factors). These also suggest the potential existence of self-selection. Thus, there are probably complicated relationships between the current car ownership and topographical factors, which need data covering on a longer period. Third, this paper has only treated four topographical factors. Other topographical factors may also be relevant: e.g., street characteristics, and availability of sidewalks. Future studies should explore a comprehensive set of topographical factors. Last but not least, it is important to reflect behavioral insights derived from the above efforts into re-design of elderly-friendly newtowns and mobility services.

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